International Gold Market

Ying Cheng, Kai Tan, Qiao Wang, and Dongfang Zhao (2014) published their time series analysis of the international gold market based on the return rate of the closing price of gold. For their analysis they classified the percent change in daily gold market price, for 1 troy ounce of gold in terms of the US dollar (the XAUUSD), into five categories: mad bear market, represents the gold index decreases significantly, bear market, the gold index declines slowly, shock market, represents the gold index fluctuates in a small scope, bull market, the gold index increases mildly, and mad bull market indicates that the gold index increases significantly. For many market investors, the international gold market is believed to have poor stability when the international economy is relatively stable. Many investors and analysts have differing beliefs about the drivers of gold. Rising US interest rates and consequently, the US dollar index, is thought to be negatively correlated with the price of international gold. However, gold is a popular investment when the international stock market becomes unstable and declines quickly (1,2). Understanding and identifying the states of the international gold market and the factors that drive them could guide investors to leverage the dynamic gold market profitably.

Data Sources

The response variable was collected and classified from usagold.com which monitors pricing discrepancies and reflects the price at which they base customer pricing. All other market data was obtained from investing.com and not necessarily real-time nor accurate.

Objective

Organizations such as R Validation Hub (pharmar.org) provides standards to assess the accuracy of R packages, and how to ensure the reproducibility and traceability of R installations, witch is necessary for the implementation of open-source R in regulated clinical trials. "*After careful consideration, the R Validation Hub concludes that there is minimal risk using these core packages for regulatory analysis and reporting*."(4) Voids in documentation and standards in contributed packages limit the functionality of the open-source statistical software R in regulated clinical trials. To address these limitations and extend the prevalence of open source solutions to the clinical setting, the R community has a collection of R packages that "share an underlying design philosophy, grammar, and data structures"(5). "*Since tidyverse is held to such* *high standards and has a large user community, the R Validation Hub members are discussing if tidyverse can be labelled as minimal risk for regularly analysis and reporting*."(4) The objective of this project is to conduct a review of current automated tools in R for model building and assessment of Multicategory Logit Models with output comparable to SAS. Due to the data context which this project was conducted, the objective was limited to the assessment of a specific Multicategory Logit Model, the Proportional Odds Cumulative Logit Model.

Initial Review

There are three popular packages available in R that provide methods for fitting Proportional Odds Cumulative Logit Models; the vglm function from the VGM library, the multinom function from the nnet library, and the plor function from the MASS library. All three of these packages are supported on The Comprehensive R Archive Network (CRAN) which requires up-to-date versions of code and documentation with a limited standard. The VGM and MASS packages are supported in the tidyverse family which requires higher standards. One advantage of the vglm function compared to plor is the ability to fit a Cumulative Logit Model with or without the proportional odds assumption. Another is that the VGM package provides more model effect testing methods such as wald.stat.vglm, lrt.stat.vglm, and score.stat.vglm. These generic functions are documented and similar output from the plor objects is not currently documented. However, one major advantage of using the plor function from the MASS library is the compatibility with the stepAIC and step procedures for automated variable selection. The three methods reviewed

Automated Stepwise Procedures

The automated stepwise procedures for Multicategory Logit Models currently available are limited to Proportional Odds Cumulative Logit Models using the plor fits. These methods cannot test the proportional odds assumption and subset model comparison at each step is restricted to AIC (or a proportional metric). Testing the proportional odds assumption is a likelihood ratio test between a model fit with and without proportional odds witch the vglm function is capable of. Another drawback of the plor fit is that estimates are inverse relations compared to those pervaded by vglm, multinom, and SAS. Four user-defined functions were created to format the final stepwise model effects and calculate hypothesis tests shown in figure 1 of the appendix. Further work is required currently, errors and warnings relating to non-converges of algorithms due to complete and quasi separation need to be addressed in a standard manner. Tests of the proportional odds could not be conducted in this study due to the data and also need to be addressed in a standard manner.

Predictions and Predictive Power

Other areas of concern for Multicategory Logit Models identified during this study are related to the response predictions and undocumented class predictions. Within the tidyverse family, the augment.plor generic function provides a single vector of fitted values for the response which is misleading and the result should be a matrix with estimated probabilities for every level of the response. Also, no documentation is available for the fitted class. A user-defined function was created that defines the class prediction for Multicategory Logit Models as the class associated with the maximum difference in predicted probability observed strata in the response. Also, a common metric for comparing models with unseen data is the harmonic mean of sensitivity and precision, the fscore. This study failed to identify a package or function to calculate the fscore in a multiclass problem. A user-defined function was created that defined multiclass sensitivity and precision to return a fscore in multiclass context. Sensitivity, the ratio of true positives over the sum of true positives and false positives, was defined as the corresponding main diagonal element over the column sum from the confusion matrix. Precision, the ratio of true negatives over the sum of true negatives and false negatives, was defined as the corresponding main diagonal element over the row sum from the confusion matrix. Figure 2 compares the undocumented class predictions from the final step model with the class prediction method defined in this paper, using a confusion matrix and calculated multiclass fscores. Much more research is needed to understand the differences between the class predictions and the validity of multiclass fscore defined in this paper.

Conclusions

Open source technology is a platform for innovation and information sharing that has accelerated human advisement and changed the world we live in. The World Wide Web was perhaps the first open information-sharing platform, created in 1989, and since 2017, net neutrality has been an ongoing battle in the United States. Corporations and enterprises feel threatened by open source technology, they strive to market innovation by restricted access to those who can afford their unbounded fees and subscriptions. It is paramount that open source solutions continue to be developed in Applied Statistics with reliability, reproducibility, and traceability. As developers and communities work together, with a common goal and standards, we will see open source implementation grow in all areas, even the clinical setting.

Appendix

Figure 1:

Model Fit Statistics

Criterion	Intercept.Only	Intercept.Covariates
AIC	1591.39	1210.3
BIC	1609.59	1246.7
Deviance	1583.39	1194.3

Global Test Null Hypothesis: BETA=0

Test	Chi.Square	DF	Pr.Chi
Likelihood Test	389.0922	4	0

Analysis of Maximum Likelihood Estimates

Parameter	Estimate	SE	Score.Stat	Pr.Chi
-2|-1	-5.3891	0.0803	8.255263e+02	0.0000
-1|0	-1.8571	0.0875	3.093165e+02	0.0000
0|1	2.0175	0.0859	3.469372e+02	0.0000
1|2	5.0386	0.0000	7.444322e+17	0.0000
US_5_Year_Bond_Yield	0.6163	0.0427	1.455250e+02	0.0000
US_Dollar_Index	3.0219	0.2242	1.340992e+02	0.0000
NAS_DAQ	-0.3434	0.1392	6.207600e+00	0.0127
Dow_Jones	0.3307	0.1903	3.084400e+00	0.0790

Odds Ratio Estimates

Effect	Point.Estimate	conf.low	conf.high
US_5_Year_Bond_Yield	1.8520	1.6802	2.0476
US_Dollar_Index	20.5294	12.2920	34.7908
NAS_DAQ	0.7094	0.5405	0.9307
Dow_Jones	1.3919	0.9603	2.0163

Figure 2

Classification Table: undocumented method predicted class

	-2	-1	0	1	2	Predicted
-2	1	1	0	0	0	2
-1	6	56	24	0	1	87
0	6	82	354	81	9	532
1	0	1	17	48	7	73
2	0	0	1	1	3	5
Actual	13	140	396	130	20	699

S ~ US_5_Year_Bond_Yield + US_Dollar_Index + NAS_DAQ + Dow_Jones

	-2	-1	0	1	2	ClassMean
sensitiviey	0.0769	0.4000	0.8939	0.3692	0.15	0.3780
precision	0.5000	0.6437	0.6654	0.6575	0.60	0.6133
fscore	0.1333	0.4934	0.7629	0.4729	0.24	0.4205

Classification Table: largest difference in predicted class probability

	-2	-1	0	1	2	Predicted
-2	2	3	0	0	0	5
-1	5	53	27	0	1	86
0	6	82	342	75	7	512
1	0	1	26	49	9	85
2	0	1	1	6	3	11
Actual	13	140	396	130	20	699

S ~ US_5_Year_Bond_Yield + US_Dollar_Index + NAS_DAQ + Dow_Jones

	-2	-1	0	1	2	ClassMean
sensitiviey	0.1538	0.3786	0.8636	0.3769	0.1500	0.3846
precision	0.4000	0.6163	0.6680	0.5765	0.2727	0.5067
fscore	0.2222	0.4690	0.7533	0.4558	0.1935	0.4188

References

1. Cheng, Ying, et al. "Analysis of the International Gold Market State Based on Markov Chain." Applied Mechanics and Materials. Vol. 687. Trans Tech Publications Ltd, 2014.

2. https://www.investopedia.com/articles/investing/100915/effect-fed-fund-rate-hikes-gold.asp

3. https://www.marketwatch.com/story/gold-prices-skid-17-lower-as-the-us-dollar-strengthens-2020-04-21?mod=mw_quote_news

4. https://www.pharmar.org/overview/

5. https://www.tidyverse.org/

https://www.usagold.com/reference/prices/goldhistory.php?ddYears=2019

https://www.investing.com/indices/major-indices